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Journal of Advanced Research in Computing and Applications

Journal homepage:
https://karyailham.com.my/index.php/arca/index
ISSN: 2462-1927

Bridging Maintenance and Troubleshooting for Enhanced System Reliability: A Review of Smart and Data-Driven Approaches

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ARTICLE INFO

Article history:
Received 10 February 2026
Received in revised form 30 May 2026
Accepted 2 June 2026
Available online 22 August 2026

ABSTRACT

This review paper examines the evolution of maintenance and troubleshooting practices and their critical role in enhancing system reliability within modern industrial environments. Traditionally, maintenance strategies such as reactive and preventive approaches were widely adopted; however, these methods often resulted in inefficiencies, unplanned downtime, and increased operational costs. With the emergence of Industry 4.0 technologies, maintenance management has transitioned toward data-driven and intelligent systems, including Computerized Maintenance Management Systems (CMMS), predictive maintenance, artificial intelligence (AI), and the Internet of Things (IoT). Despite these advancements, a significant gap remains between data generation and effective troubleshooting, primarily due to cognitive overload and limited diagnostic capabilities among technicians. This paper highlights the importance of bridging this gap through the integration of Explainable AI (XAI), augmented reality (AR), and Cognitive Digital Twins (CDT), which enhance human–machine collaboration and improve decision-making processes. Additionally, key reliability concepts such as Key Performance Indicators (KPIs), failure analysis techniques (RCA, FMEA, FTA), and Reliability-Centered Maintenance (RCM) are discussed as essential frameworks for optimizing system performance. The review also addresses current challenges in implementing smart maintenance systems, including high initial costs, data security concerns, and workforce adaptation. Furthermore, emerging trends such as blockchain, hyperautomation, and immersive training technologies are explored as future directions in maintenance management. Overall, this paper emphasizes that integrating intelligent technologies with structured maintenance strategies is essential for improving system reliability, reducing downtime, and achieving sustainable industrial performance.

Keywords:
Maintenance; systems; troubleshooting; preventive

1. Introduction

The development of the industrial revolution has significantly influenced production and maintenance processes in modern industries. Today, industries rely on advanced technologies such as automation, artificial intelligence (AI), machine learning, and real-time data [1]. However, despite

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https://doi.org/10.37934/arca.44.1.7883

these advancements, a major challenge remains: the skills gap. This refers to the mismatch between the skills employers require and those workers possess. As industries continue to evolve, workers are expected to adapt to new technologies and more complex systems [2]. In industrial maintenance, this skills gap is particularly evident in troubleshooting. While organizations use predictive maintenance systems that generate large amounts of data, they often lack the expertise and tools needed to interpret this data effectively [3]. As a result, problems such as longer equipment downtime, inefficient repairs, and over-reliance on a small number of skilled technicians occur. This gap between detecting a problem and identifying its root cause limits the full benefits of Industry 4.0 technologies [4].

Maintenance management plays a crucial role in ensuring that equipment operates efficiently and reliably. Over time, maintenance has evolved from manual inspections and experience-based decisions to data-driven and digital approaches. Technologies such as Computerized Maintenance Management Systems (CMMS) have enabled better tracking of assets, work orders, and maintenance history, supporting proactive and predictive maintenance strategies [5]. With the continued advancement of AI and the Internet of Things (IoT), maintenance is becoming more automated, intelligent, and predictive. These technologies allow early fault detection and more accurate troubleshooting, improving overall system performance [6].

System reliability refers to the ability of a system to function correctly over a specific period without failure. High reliability is essential for minimizing downtime and maintaining productivity. Maintenance helps prevent system failures, while troubleshooting focuses on identifying and resolving the root causes of problems [7]. To achieve high reliability, industries apply strategies such as predictive maintenance, condition-based monitoring, and reliability-centered maintenance (RCM). These approaches use data analysis, vibration monitoring, and thermal imaging to detect early signs of failure [8]. In addition, failure analysis methods such as Root Cause Analysis (RCA), Failure Modes and Effects Analysis (FMEA), and Fault Tree Analysis (FTA) help identify the causes of system failures.

Despite the rapid adoption of advanced technologies such as Artificial Intelligence (AI), Internet of Things (IoT), predictive maintenance, and Computerized Maintenance Management Systems (CMMS), many industries still face challenges in effectively troubleshooting equipment problems because technicians often struggle to interpret large amounts of real-time data and identify the root causes of failures [9]. Existing studies mainly focus on technological development, while limited attention is given to cognitive challenges, human–machine collaboration, and the integration of maintenance, troubleshooting, and reliability strategies into a unified framework. Therefore, this study aims to review how smart and data-driven maintenance approaches can improve troubleshooting processes and enhance system reliability in modern industries. The study examines the evolution of maintenance strategies from traditional reactive maintenance to predictive and intelligent systems, while also evaluating the role of technologies such as AI, IoT, Explainable AI (XAI), Augmented Reality (AR), and Cognitive Digital Twins (CDT) in supporting maintenance activities. In addition, the study discusses the importance of reliability tools such as Key Performance Indicators (KPIs), Root Cause Analysis (RCA), Failure Modes and Effects Analysis (FMEA), Fault Tree Analysis (FTA), and Reliability-Centered Maintenance (RCM) in improving operational performance. This study is significant because it provides a comprehensive understanding of how intelligent maintenance technologies can reduce downtime, improve troubleshooting efficiency, lower operational costs, and support safer, smarter, and more sustainable industrial systems.

2. From Skills Gap to Cognitive Gap

Modern troubleshooting challenges are no longer caused by a lack of advanced technology, but by difficulty in interpreting the large amount of data generated by these systems. Although industries now produce vast amounts of real-time data, this often leads to “data-rich but information-poor” situations [10]. Maintenance technicians are no longer relying only on intuition or manual checks; instead, they must analyse complex data such as vibration signals, thermal images, and continuous data streams. This can result in cognitive overload, where important information is hidden within excessive data. Therefore, the main challenge today is not collecting data, but understanding it. A strong data foundation is essential to reduce this gap. Traditional frameworks such as ISO 55000 remain important, but newer standards like ISO 55010:2023 emphasize aligning technical performance with financial outcomes. These standards help organizations focus on measurable value rather than simply adopting technology. Data quality is also critical [11]. The principle “garbage in, garbage out” highlights that poor-quality data leads to inaccurate results. Therefore, proper data collection, labeling, and organization are necessary. Machine learning models require accurate historical data to function effectively. Standards such as ISA-95 ensure smooth data flow from sensors to cloud systems while maintaining context and meaning [12].

Early AI systems were often criticized as “black boxes” because they provided results without explanations. Explainable AI (XAI) addresses this issue by making AI decisions transparent and understandable. This helps technicians trust the system and learn from it [13]. In addition, new training approaches such as Cognitive Digital Twins (CDT) provide realistic, virtual environments for learning. These systems simulate real-world equipment and allow users to safely practice diagnosing complex faults, improving both skills and confidence.

The most advanced stage of modern maintenance involves intelligent systems that work proactively. Cognitive Digital Twins combine AI with digital models to simulate and analyse equipment behaviour in real time [14]. They can quickly identify possible causes of faults and suggest solutions. Technologies such as federated learning further enhance these systems by allowing data sharing across organizations while maintaining privacy. Overall, combining high-quality data, explainable interfaces, and intelligent analytics creates a collaborative environment between humans and machines. This continuous learning system improves over time, making troubleshooting faster and more accurate.

Modern troubleshooting begins with reliable and well-organized data. This foundation ensures that decisions are based on accurate and meaningful information. Following proper standards helps ensure that data collected from sensors is structured and useful for both humans and AI systems [15]. Technology investments should focus on solving real problems and delivering measurable benefits. Human–technology interaction is also important. Tools such as Explainable AI help technicians understand system decisions, turning technology into a learning partner rather than a “black box”. At the same time, Augmented Reality (AR) enhances troubleshooting by displaying real-time information directly on equipment, making tasks clearer and more efficient.

This interaction creates a two-way relationship: technology supports human decision-making, while human expertise guides the system. As a result, troubleshooting becomes faster, smarter, and more effective [16]. Another key feature of this framework is continuous learning. The system records each failure, the actions taken, and the outcomes. This information is then used to improve AI models and digital twins. Over time, the system becomes more accurate and reliable. In summary, modern troubleshooting integrates high-quality data, intelligent tools, and human expertise into a continuous improvement cycle. This creates a self-improving system that enhances efficiency and has the potential to close the troubleshooting gap.

3. Maintenance

In early industrial practices, most organizations relied on reactive maintenance, where equipment is repaired only after failure occurs. This approach requires minimal planning and tools, but it is highly unreliable as it does not monitor equipment condition. Although reactive maintenance may appear cost-effective initially, it often leads to higher long-term costs due to unexpected breakdowns, expensive emergency repairs, and prolonged downtime. It can also disrupt production, reduce revenue, and increase safety risks. As machinery becomes more complex, this approach is no longer sustainable. Preventive maintenance involves scheduled servicing to reduce the likelihood of equipment failure. It helps detect minor issues early, improves reliability, and extends equipment lifespan. However, this approach is based on fixed schedules rather than actual equipment condition, which may lead to unnecessary maintenance (over-maintenance). These limitations contributed to the development of more advanced systems such as Computerized Maintenance Management Systems (CMMS) [17].

Cloud-based CMMS allows real-time data access, remote monitoring, and efficient management of maintenance activities. It ensures up-to-date information, faster decision-making, and improved coordination. These systems also provide automatic updates and strong cybersecurity features such as data encryption and access control. As a result, cloud-based CMMS offers a flexible, secure, and modern approach to maintenance management. Predictive maintenance uses AI and machine learning to analyse real-time and historical data to detect early signs of failure. It allows maintenance to be performed only when necessary, reducing downtime and maintenance costs. This approach improves efficiency, optimizes resource usage, and enhances overall system performance by preventing unexpected failures. Modern maintenance systems are integrated with other business platforms such as ERP and inventory systems. This integration improves communication, coordination, and decision-making across departments. It also helps ensure spare parts availability, better cost tracking, and alignment of maintenance activities with business goals.

Implementing digital maintenance solutions requires significant investment in technology, infrastructure, and training. These high upfront costs can be challenging, especially for small organizations. The use of IoT and cloud systems increases the risk of cybersecurity threats and data breaches. Protecting sensitive maintenance data is critical to ensure system reliability and business continuity. Adopting new technologies requires proper training and a shift in organizational culture. Resistance to change and lack of skills can slow down implementation. Effective training and communication are essential for successful adoption [18].

Blockchain technology provides a secure and transparent way to store maintenance records. It ensures data accuracy and prevents unauthorized changes, improving trust and reliability. AR enhances maintenance by providing real-time visual guidance to technicians. It improves accuracy, reduces errors, and supports training by offering interactive learning experiences. Hyperautomation combines AI, IoT, and automation technologies to fully automate maintenance processes. It enables predictive diagnostics, automated workflows, and continuous monitoring, leading to improved efficiency and reduced costs.

4. Key Performance Indicators for System Reliability

Key Performance Indicators (KPIs) are measurable values used to evaluate how well a system meets its reliability goals. In maintenance engineering, KPIs help monitor system performance and identify weaknesses. Common KPIs include Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), availability, and failure rate. MTBF refers to the average time a system operates before failure, while MTTR measures the time required to repair and restore the system. System availability depends on both MTBF and MTTR and can be expressed as:

$$A=\frac{\text{MTBF}}{\text{MTBF}+\text{MTTR}} \tag{1}$$

A higher availability value indicates a more reliable and efficiently maintained system. Another important KPI is the failure rate (λ), which shows how frequently failures occur over time. These indicators support better decision-making, maintenance planning, and resource allocation. Failure analysis is used to identify the causes of system failures and prevent them from recurring. Common methods include Root Cause Analysis (RCA), Failure Modes and Effects Analysis (FMEA), and Fault Tree Analysis (FTA). RCA focuses on identifying the main cause of a failure rather than just its symptoms. FMEA evaluates possible failure modes, their causes, and their impact, allowing maintenance teams to prioritize risks [19]. FTA uses a graphical approach to show how different factors contribute to system failure and helps calculate failure probabilities. These methods allow engineers to shift from reactive maintenance to proactive strategies by preventing failures before they occur.

Reliability-Centered Maintenance (RCM) is a structured approach used to determine the most effective maintenance strategies for ensuring system reliability. It analyses how equipment functions, how it can fail, and the consequences of those failures. The RCM process includes identifying critical equipment, analysing failure modes using tools such as FMEA and RCA, evaluating the impact of failures, and selecting appropriate maintenance strategies. These strategies may include preventive, predictive, or corrective maintenance depending on the situation. RCM emphasizes proactive maintenance by combining different maintenance approaches. Preventive maintenance involves scheduled servicing, predictive maintenance uses data and sensors to detect potential failures, and corrective maintenance restores systems after failure. By implementing RCM, organizations can optimize maintenance resources, reduce downtime, improve safety, and extend the lifespan of equipment [20]. It also supports better compliance with reliability standards across various industries.

5. Conclusion

The integration of artificial intelligence (AI) with human expertise is transforming maintenance and troubleshooting. This shift is not a minor improvement but a major change toward smarter, more collaborative systems. Modern technologies such as predictive analytics and digital twins are evolving from simple diagnostic tools into intelligent systems that support decision-making. At the same time, training methods are moving toward continuous learning through realistic, AI-based simulations. Organizations that build strong data foundations, promote human–AI collaboration, and adopt adaptive technologies will be better prepared for future challenges. The goal of modern troubleshooting is not only to fix problems faster but to better understand system behaviour, leading to improved reliability and performance.

Maintenance management has evolved from traditional reactive and preventive approaches to modern, digital systems. Technologies such as cloud-based CMMS, AI, IoT, and system integration have significantly improved efficiency and accuracy. However, challenges such as high implementation costs, data security risks, and workforce adaptation remain. These challenges can be addressed through proper planning, strong cybersecurity measures, and effective training. Emerging technologies such as blockchain, Augmented Reality (AR), and hyperautomation will continue to drive maintenance toward more intelligent and automated systems.

System reliability remains a key factor in achieving operational excellence. It ensures consistent performance, reduces downtime, and lowers operational costs. This review highlights the importance of Key Performance Indicators (KPIs), failure analysis methods (such as RCA and FMEA), and Reliability-Centered Maintenance (RCM) in improving system reliability. In addition, modern technologies enable a shift from reactive to predictive maintenance through real-time monitoring and data analysis. Overall, achieving high system reliability enhances efficiency, safety, and sustainability. It also supports long-term asset performance and strengthens an organization's competitiveness in modern industries.

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